IBM Watson IoT

IoT for insurance:

A case for

Complex event processing

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1/18/17

Motivation

Top 5 Benefits of IoT to the Financial Services Industry

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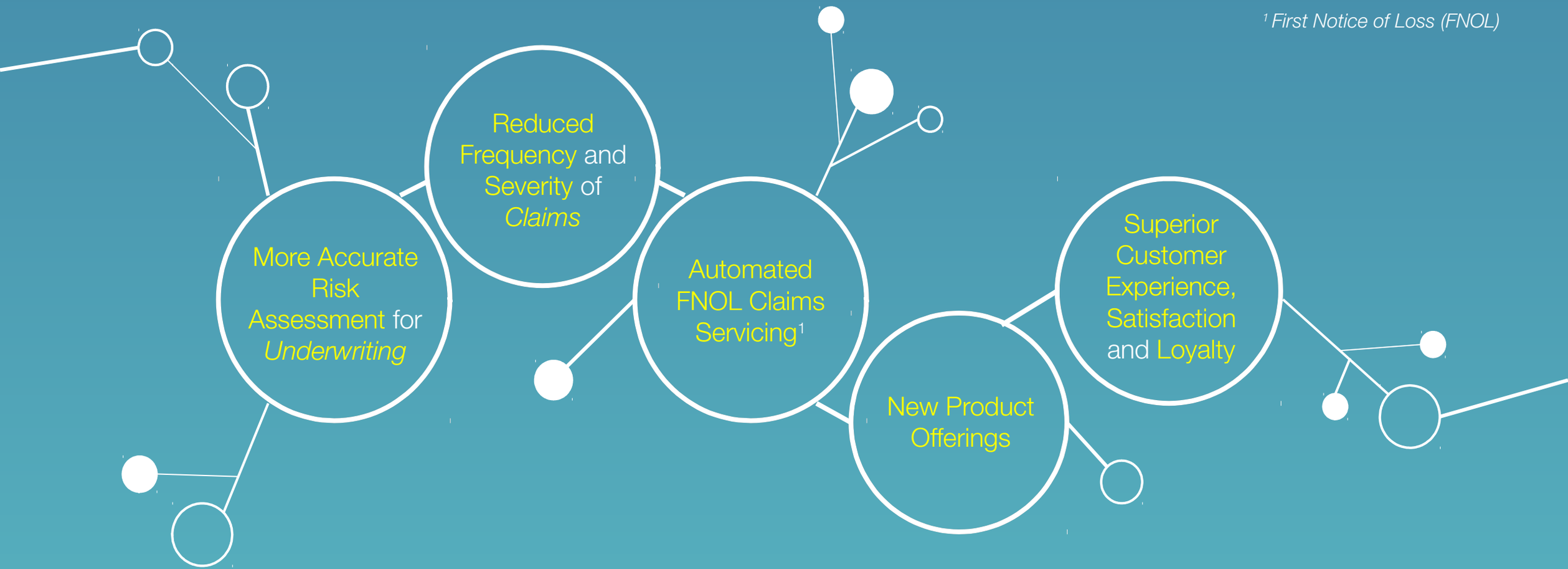
What we learn from the physical world will transform several industries, including the Insurance Sector in which IoT will have one of the greatest impacts.



[1] First Notice of Loss (FNOL)

Insurance Industry Transformation to Proactive Protection & Claims Avoidance

Carriers are transforming their historic risk assessment models by proactively mitigating risk through real time alerts and analytics

Protected Wellness / Workers

Safety
Health

Protected Home & Buildings

Homes
Ships
Factories
Warehouses
Construction Sites
Commercial Office

Protected Lifestyle & Business

Risks
Assets
Finances

Contextual Insights

Analysis

Real-time Monitoring

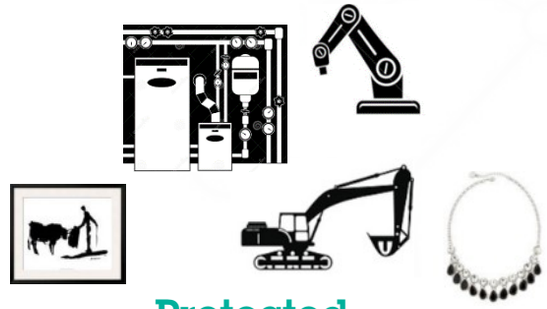
Alerts

Protected Environment

Weather
Construction
Crime

Protected Cars / Fleet

Driver Profiles
Telematics
Mapping



Protected Assets & Equipment

Predictive Maintenance
Authorized Access
Location

IBM IoT for Insurance – How it works

Connected Auto

Wearables/ Sensors

Smart Home Hub

IoT Device & Equipment Vendors

1

Insurance Holder registers Sensors / Hub/Wearables via IoT

2

Data streams into Watson IoT Platform providing Insurers data

developerWorks. Recipes

Watson IoT Platform

The Weather Company

IBM Watson Analytics

3

Advanced Analytics and Shields of protection produce Actions such as Driver Behavior, Leak Detection, Worker Fatigue

4

Consumer and Claims Adjusters can manage actions, perform device command and control functions

Insurance shield example

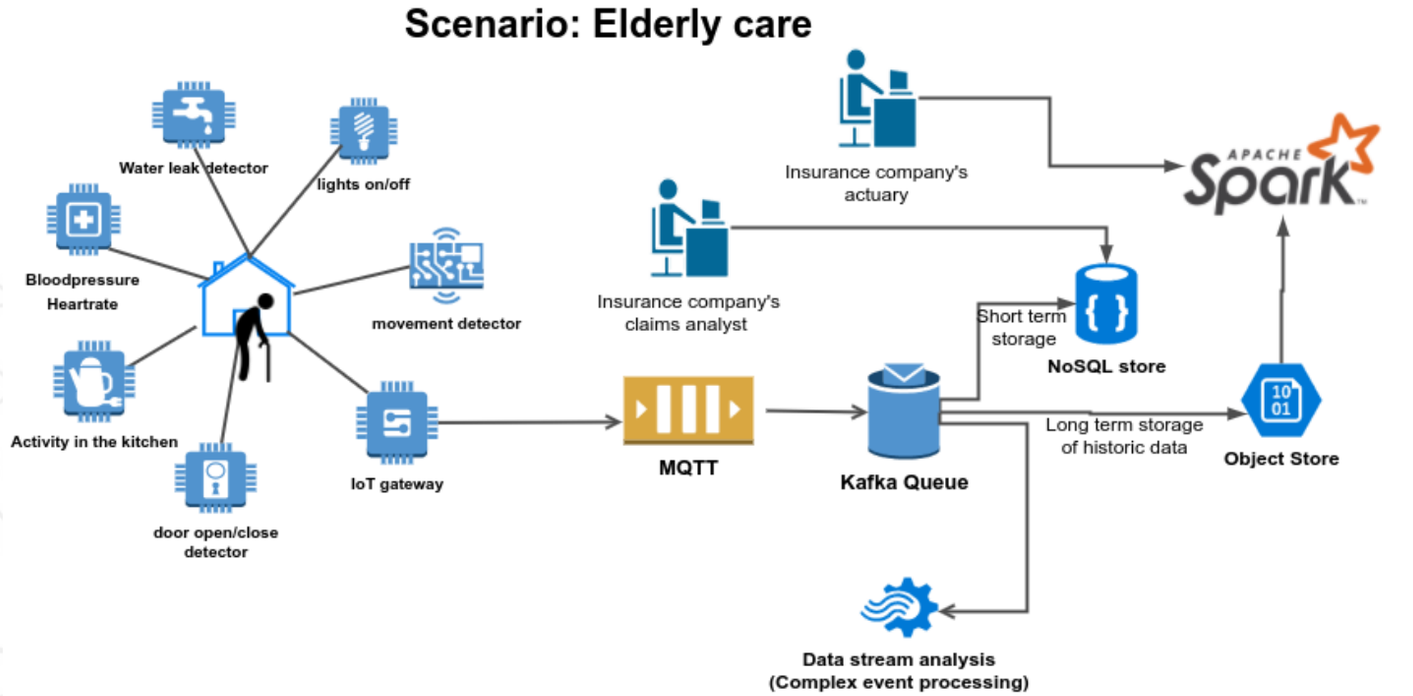
"Door opens at night"

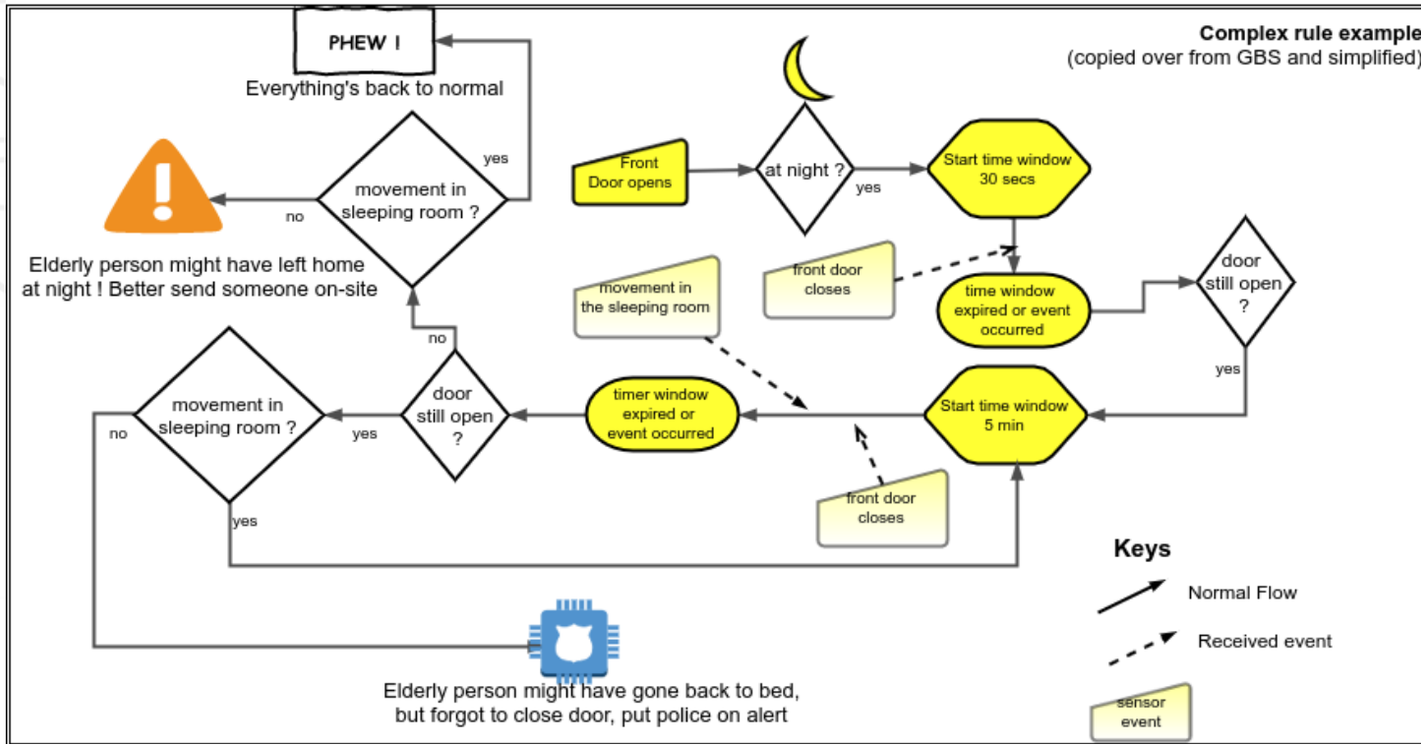
Evaluating this rather convoluted shield gives rise to Complex Event Processing:

Requirement:

- Stateful processing
- Sliding windows

Other shields like "heart rate monitoring" make use of tumbling windows.





See also here
https://i.stack.imgur.com/mm06A.jpg
For windowing in data stream processing

Insurance shields examples in more details


Hazard Detection

Check conditions

Expedite Response/Alerts

Simple Shields: Rule base , Multi sensor , Time window

Detect "Water leak" hazard if water sensor == wet for last 4 minutes && water valve == close	Check: (location == @home) && (08:00 < now < 18:30)	send push notification to Insured.phone-number
Detect "overexertion" hazard if last 20 reading of heart-rate > 80 && Heat index > 80	Check: (location == @work) && (23:00 < now < 05:00)	send push notification to Employee.supervisor.phone-number

Complex Shield: ML , Aggregations, Personalization

Detect "Anomaly Water leak" risk 2 or water sensor == wet for last 30 sec && water valve == open && current temp < avg temp + 20 && weather == dry	Check: (location != @home) && (08:00 < now < 18:30)	send push notification to Insured.phone-number send SMS to available plumber.phone-number
Detect "overexertion" hazard if last 20 readings (heart-rate) > Avg Rest HR && normal heat index for location> 80	Check: (location == @work) && (23:00 < now < 05:00)	send push notification to Employee.supervisor.phone-number

Cognitive Shield : Cognitive Diagnostics , Pattern Recognition (Activity, Gestures) , Shields Personalization , Offline Learning

Prevent "Heat Stress" hazard

If user spent last 30 minutes at heat index > 85 && and user situation is "intensive physical working" , and body temp > avg body temp for "intensive physical working" activity || body temp > body temp at beginning of shift + 3
&& User specify "dry throats" and drowsiness && system didn't capture water intake gestures

Technical background

Complex event processing in a nutshell

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Events

exhibit the following characteristics. They

- Are **Immutable**
- Have **strong temporal constraints**
- Have a **managed lifecycle** (become “stale” after some time) and thus as subject to a **sliding window** of ‘validity’.

In the IOT case events have some ‘sparseness’ traits, so

- There is a **high volume** of events.
- **Patterns** are more important than invidual events.

Event Processing

is a method of tracking and analyzing (processing) streams of information (data) about things that happen (events),[1] and deriving a conclusion from them.

Complex Event Processing

or CEP, is event processing that combines data from multiple sources to infer events or patterns that suggest more complicated circumstances. The goal of complex event processing is to identify meaningful events (such as opportunities or threats) and respond to them as quickly as possible.

Traits/functional requirements

- Allow detection, correlation, aggregation and composition of events.
- Support processing of Streams of events.
- Support temporal constraints in order to model the temporal relationships between events.
- Support sliding windows of interesting events.
- Support a properly scoped unified clock - in the case mentioned in the deck the proper scope would be all sensors in the belderly person's apartment.
- Support the required volumes of events for CEP use cases.
- Support MQTT for event input into the engine.

For background see wikipedia.org

Requirements for complex event processing

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“At least once” guarantee

No IoT event must get lost before being processed. IoT events must be retained/buffered until handled otherwise we could lose events, resp. do not sent out actions
Note that this implies **fault tolerance**, i.e. restartability while preserving its internal state.

Partial ordering guarantee

Events for a particular group of devices (for example grouped by ownership) must be delivered and processed in order.
→ See elderly care example.

“Exactly once” guarantee

No action must be triggered twice.

Scalability

CEP must scale with number of users and event rate.

Latency

Actions must be triggered in less than 10 secs.
This ballpark figure reflects the near-realtime characteristics tempered with the latency of external components (e.g. network). Note that latency guarantees imply **availability**.

For background and terminology
see https://dzone.com/articles/kafka-clients-at-most-once-at-least-once-exactly-o

Supports modular programming model

Adding/Modifying a shield (specific complex event evaluation) should not affect other shields (Modular development, test and deployment)

Modification without outage

Adding/Modifying a shield should be possible without stopping the execution of this shield.

Rule Editor

Shield development & deployment should be easy.

Low Dev/Test effort

Shield engine development effort should be as low as possible

Low Total cost of ownership

Operations (monitoring & runbooks) and maintenance costs should be as low as possible

Automated instance deployment

This either means a multi-tenant solution where instance creation doesn't affect deployment or we need a fully automated true deployment. The former requires tenant isolation, the latter either a bluemix service or well designed setup 'scripts'. Upgrade without downtime is subsumed here.

Cost

Costs for components used to deploy the shield engine should be as low as possible.

Fault tolerance – pattern matching state engine data

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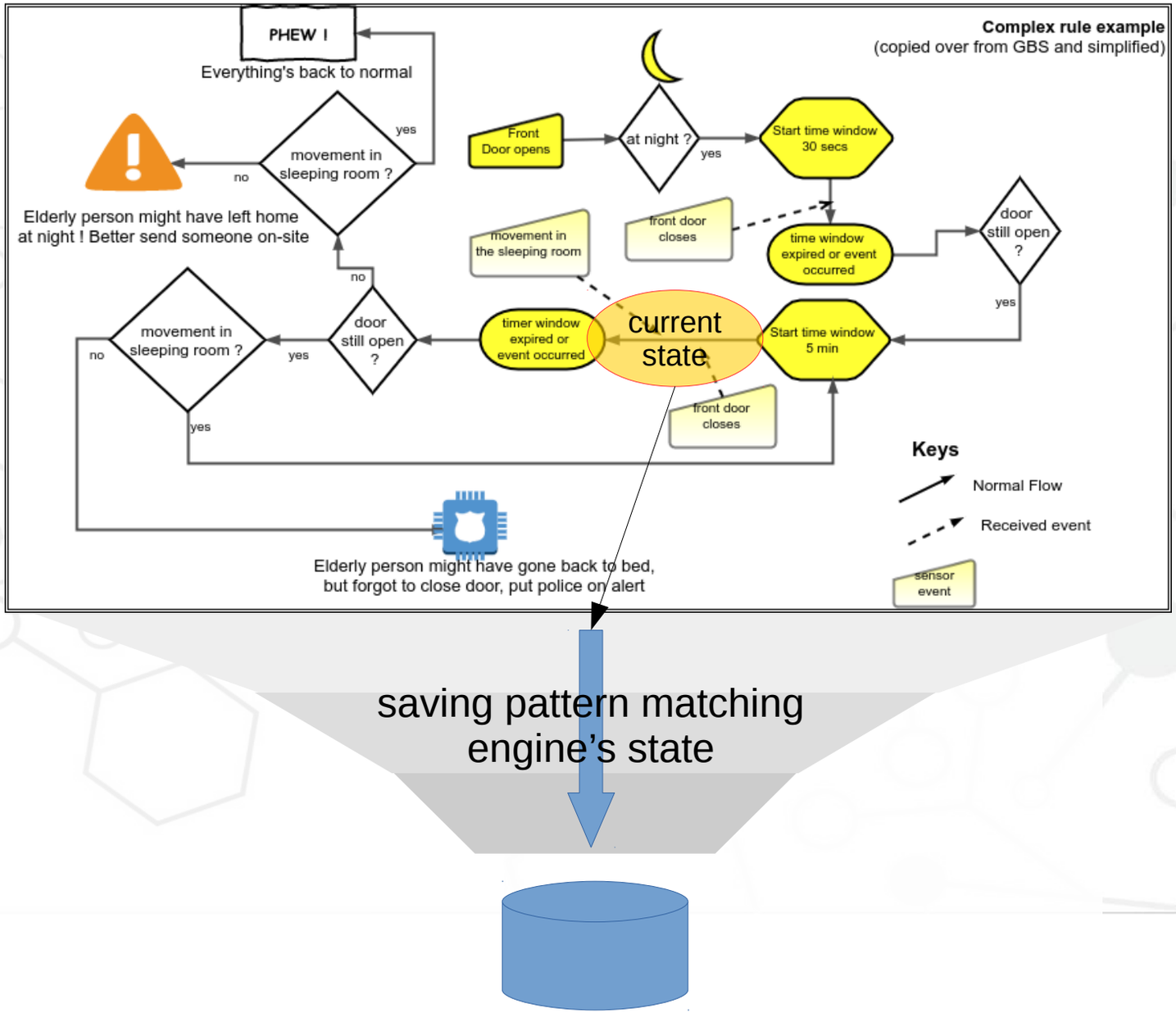
Considerations:

Saving state vs. periodic checkpointing vs. saving event offsets

- Saving state requires a write operation after applying operators in the pattern matching, so we get many small write operations.
- Saving event offset of the event when the state engine was in initial state requires the event source to maintain persistency and runs the risk of duplicate actions
- Periodic Checkpointing covers the middle ground

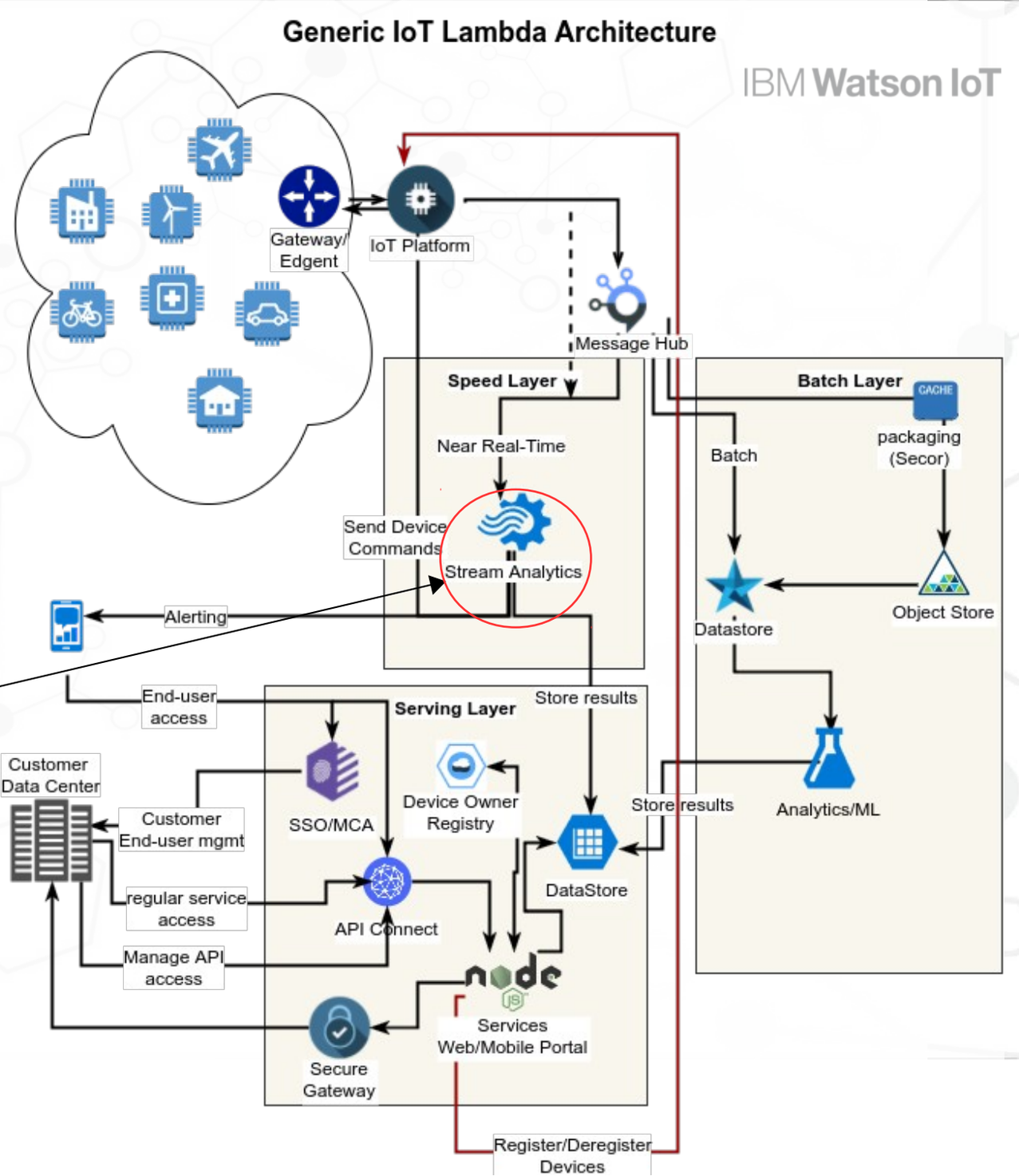
What datamodel is the best fit ?

- Saving offsets requires minimal amount of data, basically a triple of shield, user and queue offset to the last terminal event that causes a transition of the state engine to initial state.
- Saving state or checkpointing results in unstructured data best suited for flat files or a NoSQL database.



Complex Event Processing in an IoT context/architecture

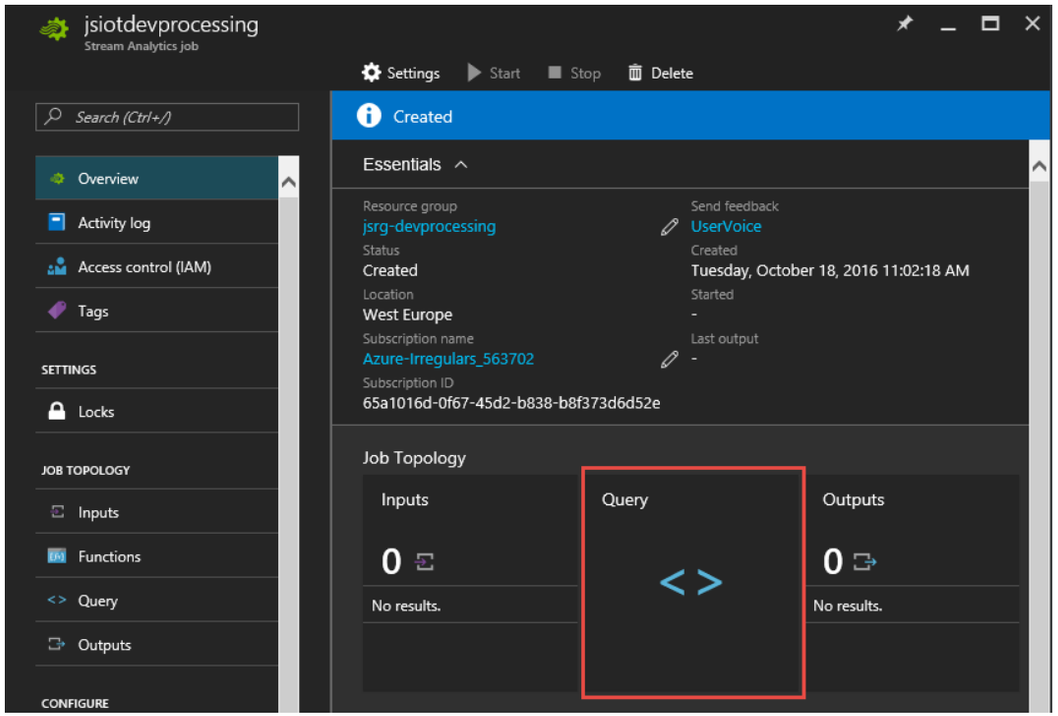
Complex Event Processing typically needs to be executed near real-time as close as possible to the event sources, so in a Lambda architecture it takes place **here**



Selecting candidates

Setting the stage – Azure Stream Analytics

IoT Events



Query: Alert to trigger a business workflow

Need help with your query? Check out some of the most common Stream Analytics query patterns here.

```
1  SELECT
2      System.Timestamp AS OutputTime,
3      dspl AS SensorName,
4      Avg(temp) AS AvgTemperature
5  INTO
6     output
7  FROM
8      InputStream TIMESTAMP BY time
9  GROUP BY TumblingWindow(second,30),dspl
10 HAVING Avg(temp)>100
```

Your query could be put in logs that are in a potentially different geography.
Missing some language constructs? Let us know! (Powered by UserVoice - Privacy Policy)

Results

output

Tumbling Window

Query: Detect absence of events

Need help with your query? Check out some of the most common Stream Analytics query patterns here.

```
1  SELECT
2      t1.time,
3      t1.dspl AS SensorName
4  INTO
5     output
6  FROM
7      InputStream t1 TIMESTAMP BY time
8  LEFT OUTER JOIN InputStream t2 TIMESTAMP BY time
9  ON
10     t1.dspl=t2.dspl AND
11     DATEDIFF(second,t1,t2) BETWEEN 1 and 5
12 WHERE t2.dspl IS NULL
```

Your query could be put in logs that are in a potentially different geography.
Missing some language constructs? Let us know! (Powered by UserVoice - Privacy Policy)

Results

output

Compare filtered with non-filtered output (based on timestamps)

https://docs.microsoft.com/en-us/azure/stream-analytics/stream-analytics-build-an-iot-solution-using-stream-analytics

Open Source frameworks for handling stream data

	Flume	NiFi	Gearpump	Apex	Kafka Streams	Spark Streaming	Storm	Storm + Trident	Samza	Flink	Ignite Streaming	Beam (*GC DataFlow)
Current version	1.6.0	0.6.1	incubating	3.3.0	0.9.0.1* (available in 0.10)	1.6.1	1.0.0	1.0.0	0.10.0	1.0.2	1.5.0	incubating
Category	DC/SEP	DC/SEP	SEP	DC/ESP	ESP	ESP	ESP/CEP	ESP/CEP	ESP	ESP/CEP	ESP/CEP	SDK
Event size	single	single	single	single	single	micro-batch	single	mini-batch	single	single	single	single
Available since (incubator since)	June 2012 (June 2011)	July 2015 (Nov 2014)	(Mar 2016)	Apr 2016 (Aug 2015)	Apr 2016 (July 2011)	Feb 2014 (2013)	Sep 2014 (Sep 2013)	Sep 2014 (Sep 2013)	Jan 2014 (July 2013)	Dec 2014 (Mar 2014)	Sep 2015 (Oct 2014)	(Feb 2016)
Contributors	26	67	19	53	160	838	207	207	48	159	56	80
Main backers	Apple Cloudera	Hortonworks	Intel Lightbend	Data Torrent	Confluent	AMPLab Databricks	Backtype Twitter	Backtype Twitter	LinkedIn	dataArtisans	GridGain	Google
Delivery guarantees	at least once	at least once	exactly once at least once (with non-fault-tolerant sources)	exactly once	at least once	exactly once at least once (with non-fault-tolerant sources)	at least once	exactly once	at least once	exactly once	at least once	exactly once*
State management	transactional updates	local and distributed snapshots	checkpoints	checkpoints	local and distributed snapshots	checkpoints	record acknowledgements	record acknowledgements	local snapshots distributed snapshots (fault-tolerant)	distributed snapshots	checkpoints	transactional updates*
Fault tolerance	yes (with file channel only)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes*
Out-of-order processing	no	no	yes	no	yes	no	yes	yes	yes (but not within a single partition)	yes	yes	yes*
Event prioritization	no	yes	programmable	programmable	programmable	programmable	programmable	programmable	yes	programmable	programmable	programmable
Windowing	no	no	time-based	time-based	time-based	time-based	time-based count-based	time-based count-based	time-based	time-based count-based	time-based count-based	time-based
Back-pressure	no	yes	yes	yes	N/A	yes	yes	yes	yes	yes	yes	yes*
Primary abstraction	Event	FlowFile	Message	Tuple	KafkaStream	DStream	Tuple	TridentTuple	Message	DataStream	IgniteDataStreamer	PCollection
Data flow	agent	flow (process group)	streaming application	streaming application	process topology	application	topology	topology	job	streaming dataflow	job	pipeline
Latency	low	configurable	very low	very low	very low	medium	very low	medium	low	low (configurable)	very low	low*
Resource management	native	native	YARN	YARN	Any process manager (e.g. YARN, Mesos, Chef, Puppet, Salt, Kubernetes, ...)	YARN Mesos	YARN Mesos	YARN Mesos	YARN	YARN	YARN Mesos	integrated*
Auto-scaling	no	no	no	yes	yes	yes	no	no	no	no	no	yes*
In-flight modifications	no	yes	yes	yes	yes	no	yes (for resources)	yes (for resources)	no	no	no	no
API	declarative	compositional	declarative	declarative	declarative	declarative	compositional	compositional	compositional	declarative	declarative	declarative
Primarily written in	Java	Java	Scala	Java	Java	Scala	Clojure	Java	Scala	Java	Java	Java
API languages	text files Java	REST (GUI)	Scala Java	Java	Java	Scala Java Python	Scala Java Clojure Python Ruby	Java Python Scala	Java	Java Scala Python	Java .NET C++	Java*
Notable users	Meebo Sharethrough SimpleGeo	N/A	Intel Levi's Honeywell	Capital One GE Predix PubMatic	N/A	Kelkoo Localytics AsiaInfo Opentable Fairndata Guavus	Yahoo! Spotify Groupon Flipboard The Weather Channel Alibaba Baidu Yelp	Klout GumGum CrowdFlower	LinkedIn Netflix Intuit Uber	King Otto Group	GridGain	N/A

Taken from Ian Hellström, https://databaseline.wordpress.com/2016/03/12/an-overview-of-apache-streaming-technologies/

Approach #1: Kafka shield engine

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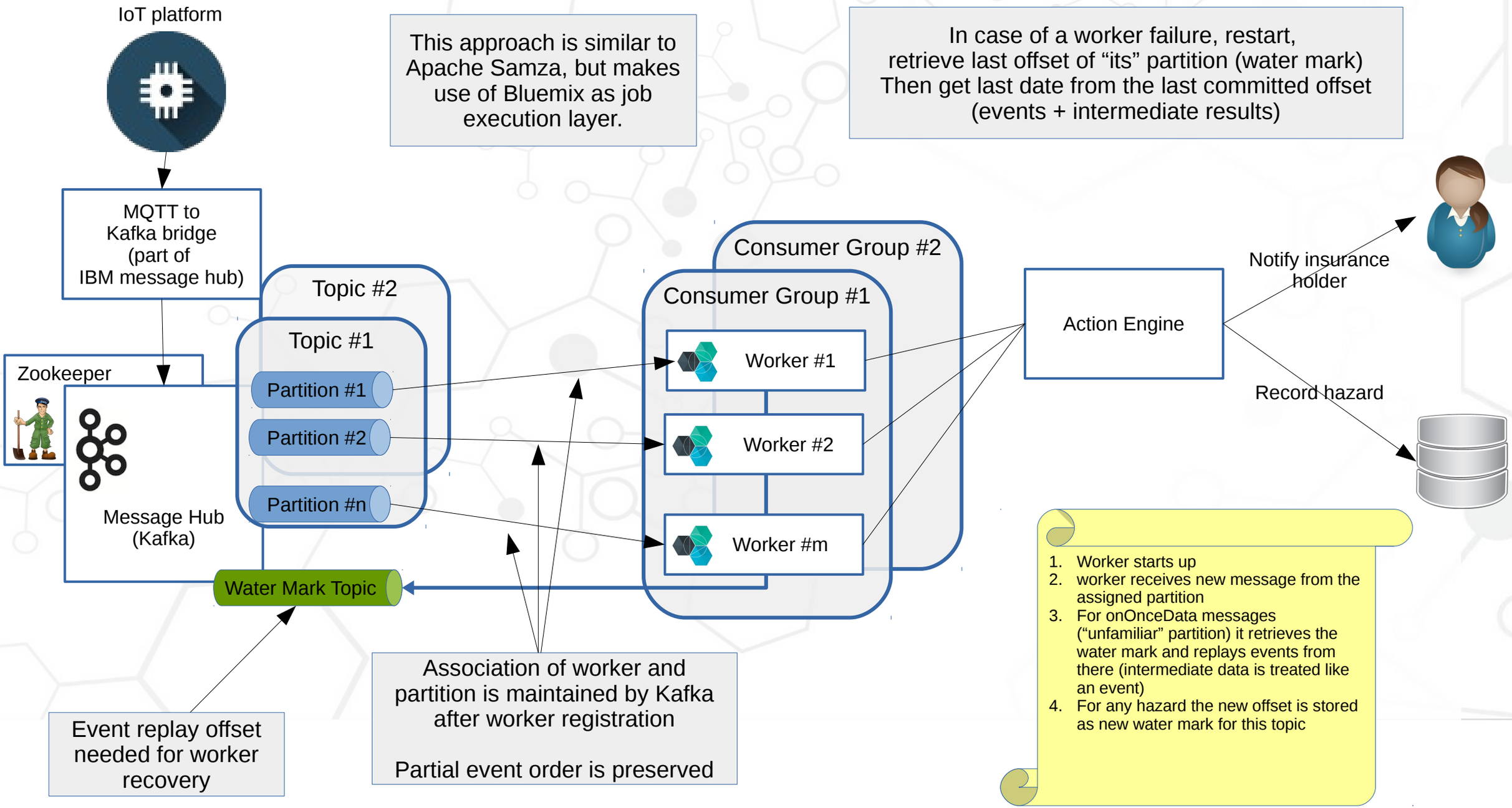
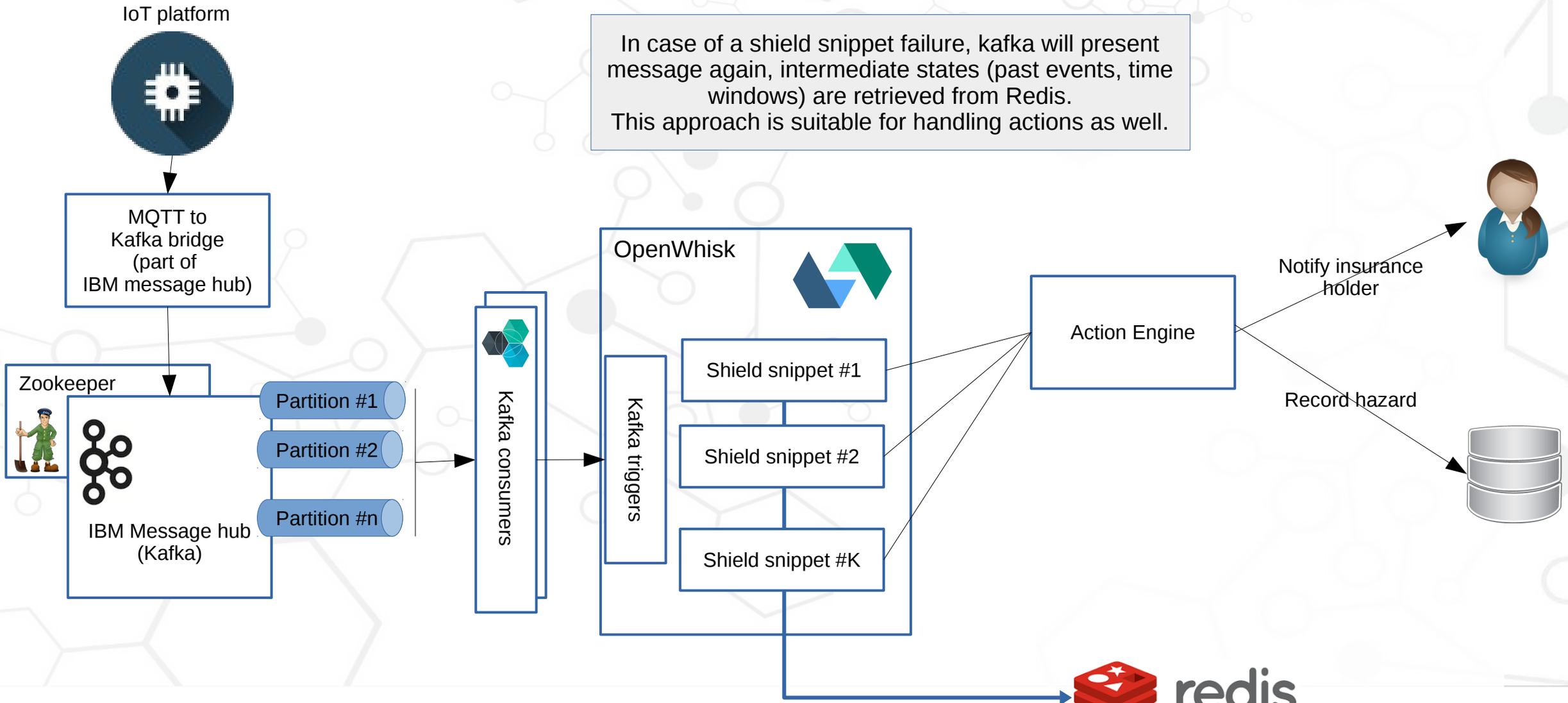


Approach #2: OpenWhisk shield dispatcher on Kafka

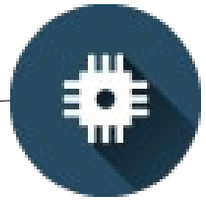
IBM Watson IoT



This approach violates the partial event ordering guarantee

Approach #3: Apache Flink with Kafka connector

IBM Watson IoT



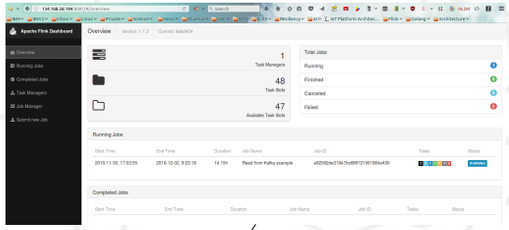
IoT platform

MQTT to Kafka bridge (part of IBM message hub)

Zookeeper

Message Hub (Kafka)

Consume and analyze event stream from Kafka topic



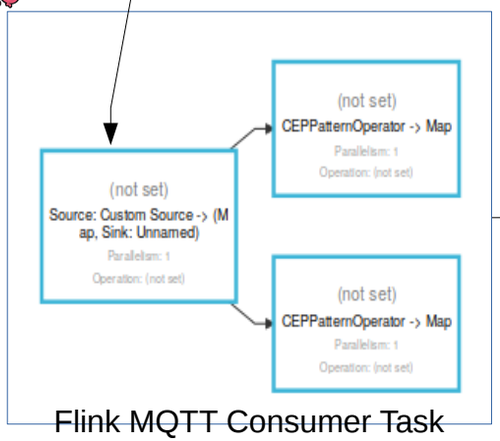
Submit Shield Jobs:
One MQTT Consumer Job per Shield !

Flink Jobmanager

Instantiate Kafka Consumer

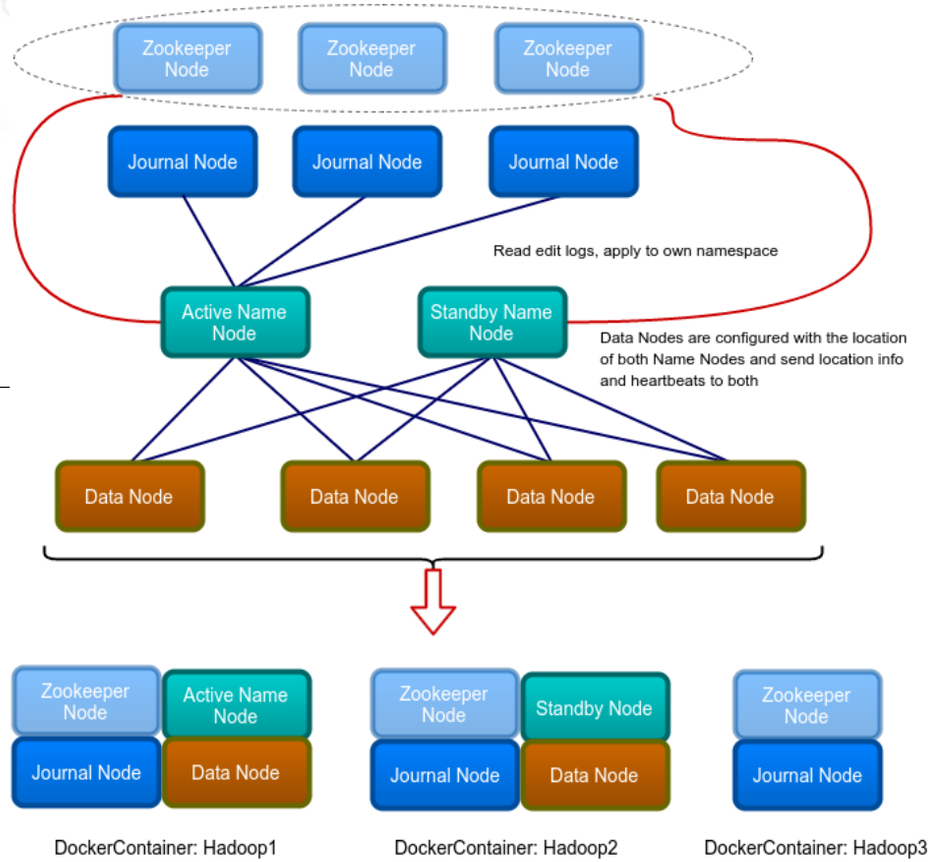
Rely on YARN for restart and on HDFS for Checkpointing

Flink Taskmanager(s)



Flink MQTT Consumer Task

Hadoop HA based on Quorum of Journal Managers and Zookeeper



Scaling considerations:

Flink job optimizer computes job parallelization plan during deployment, but requires restart to rescale later on:
http://de.slideshare.net/tillrohrmann/dynamic-scaling-how-apache-flink-adapts-to-changing-workloads

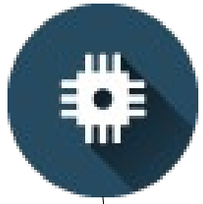
MQTT Backpressure considerations:

Flink checkpoints every 5 secs by default, IoT4I expects < 120 evts/sec, with a dedicated IoT platform MQTT broker we're well below the limit of 5000 retained messages (Watson IoTP)

See the following NewRelic presentation for a real life data aggregation show case
http://berlin.flink-forward.org/wp-content/uploads/2016/07/Ron-Crocker-Evaluating-Streaming-Framework-Performance-for-a-Large-Scale-Aggregation-Pipeline.pdf

Approach #4: Apache Spark Streaming with Kafka connector

IBM Watson IoT



MQTT to
Kafka bridge
(part of
IBM message hub)

Zookeeper

Message Hub
(Kafka)

```
$ ./bin/spark-submit --class org.apache.spark.examples.SparkPi \
    --master yarn \
    --deploy-mode cluster \
    --driver-memory 4g \
    --executor-memory 2g \
    --executor-cores 1 \
    --queue thequeue \
    lib/spark-examples*.jar \
    10
```

Submit Kafka
Consumer Jobs

Spark Driver Program

Spark Context

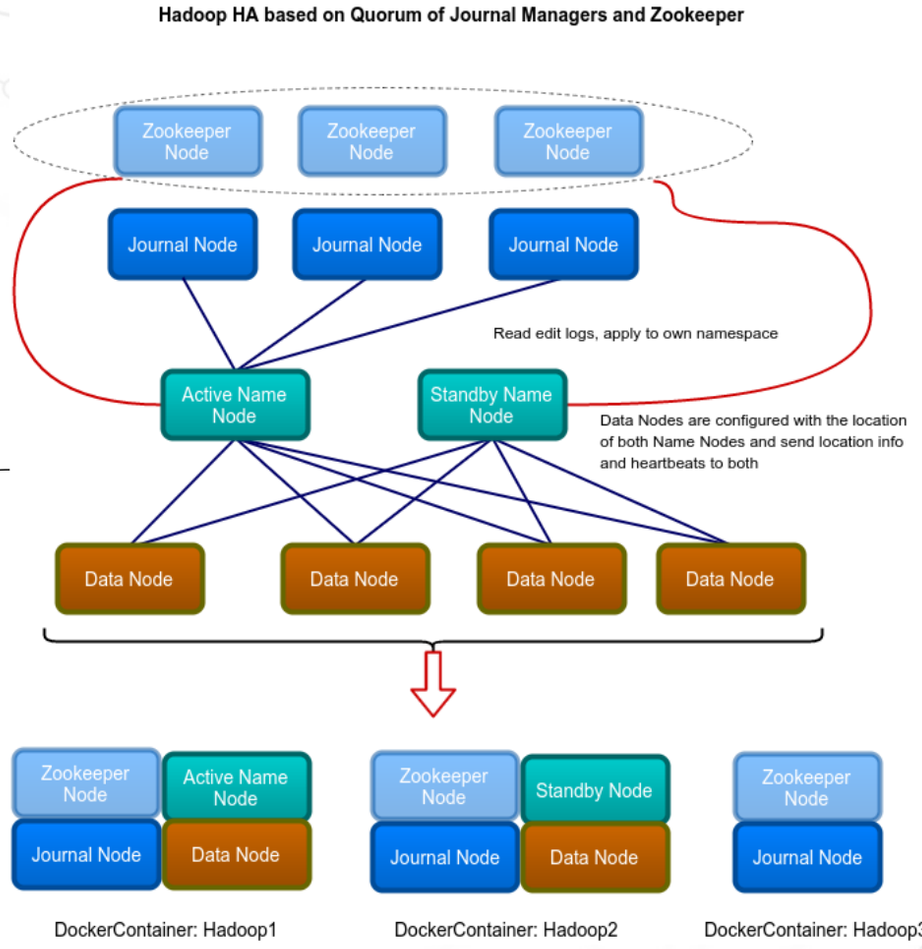
Rely on YARN
for restart and
on HDFS for
Checkpointing

Instantiate Kafka
Consumer Task

Consume and analyze
Kafka topic event stream

Spark Task Manager

Spark Task



Backpressure considerations:

Spark makes use of microbatching over D(istributed)Streams, an ensemble of Resilient Distributed Datasets that can be checkpointed; period depends on the DStream's granularity (default interval 10sec; checkpointing is a multiple of that, so >= 10 secs). IoT4I expects < 120 evts/sec, with a dedicated IoT platform MQTT broker + Kafka Hub we're well below the event rate that can be consumed by a regular Spark Streaming Task.
BTW, the current MQTT Spark consumer (Bahir) does not support back pressure, so Kafka is required here

For background see
http://spark.apache.org/docs/latest/streaming-programming-guide.htm
http://spark.apache.org/docs/latest/running-on-yarn.html

Approach #5: Agent framework based shield dispatcher on MQTT

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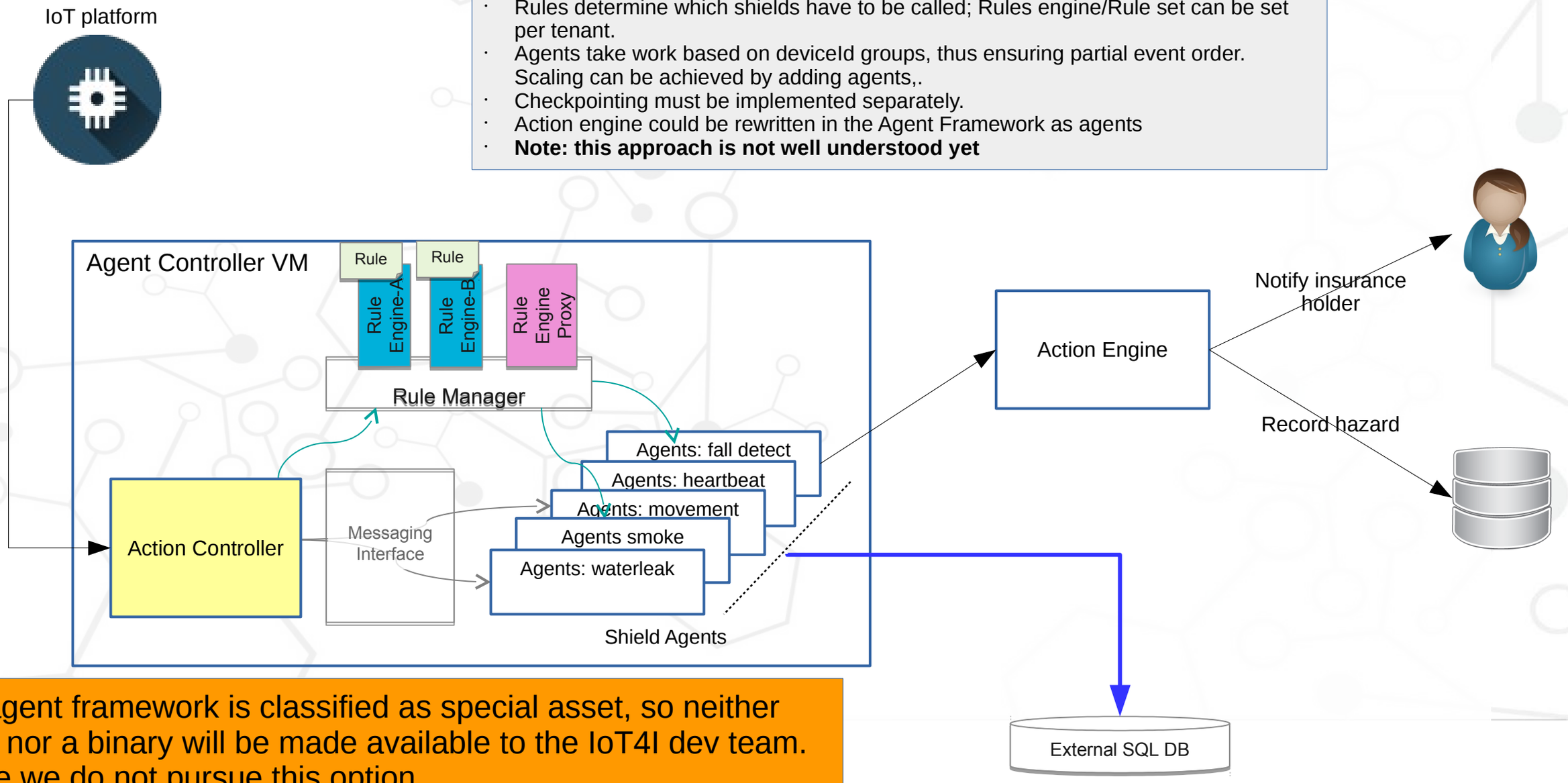
Considerations

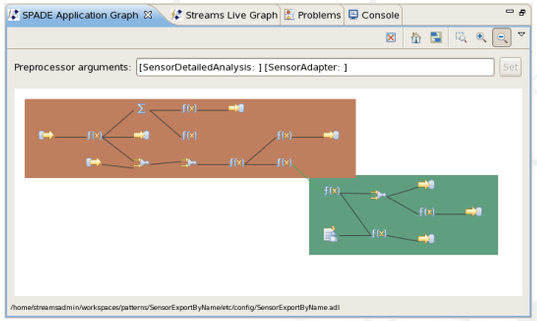
- Rules determine which shields have to be called; Rules engine/Rule set can be set per tenant.
- Agents take work based on deviceId groups, thus ensuring partial event order. Scaling can be achieved by adding agents,.
- Checkpointing must be implemented separately.
- Action engine could be rewritten in the Agent Framework as agents
- **Note: this approach is not well understood yet**



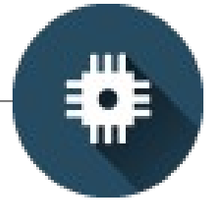
The agent framework is classified as special asset, so neither code, nor a binary will be made available to the IoT4I dev team. Hence we do not pursue this option

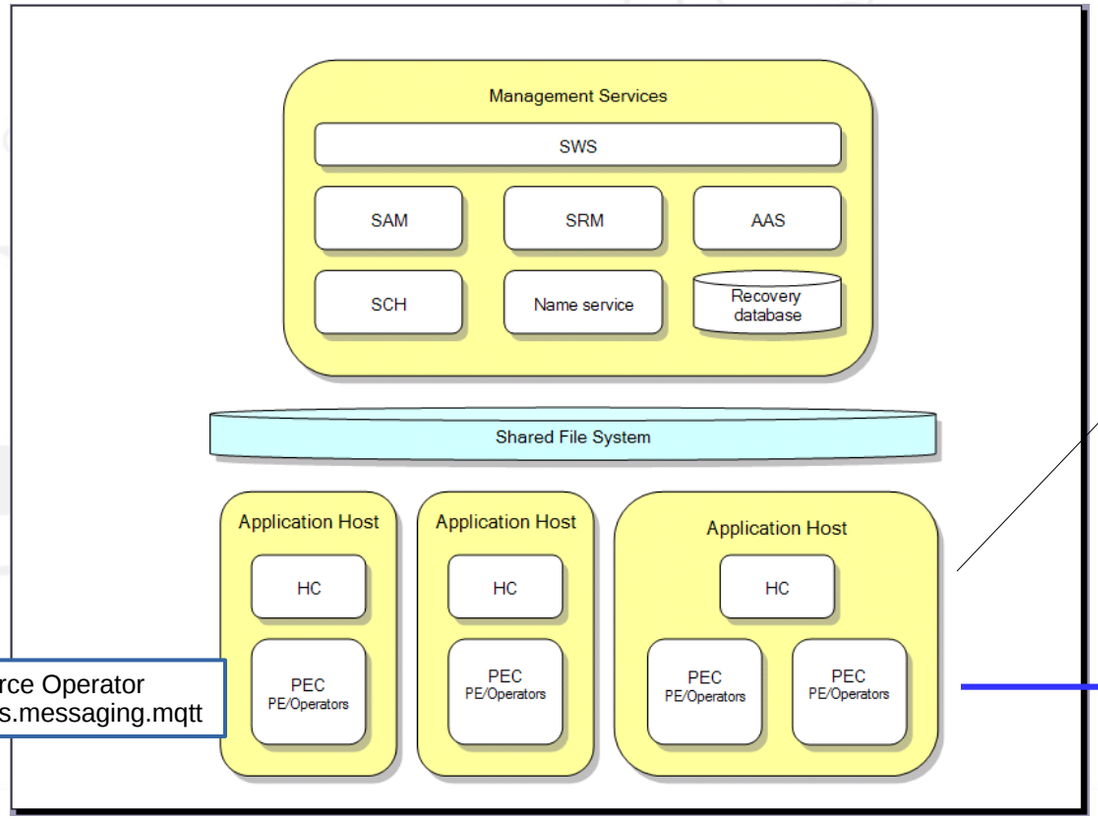
Approach #6: IBM Streams

IBM Watson IoT



IoT platform





MQTT Source Operator
com.ibm.streams.messaging.mqtt

Action Engine

Notify insurance holder

Record hazard

External SQL DB

Approach #7: ODM Decision Server Insights

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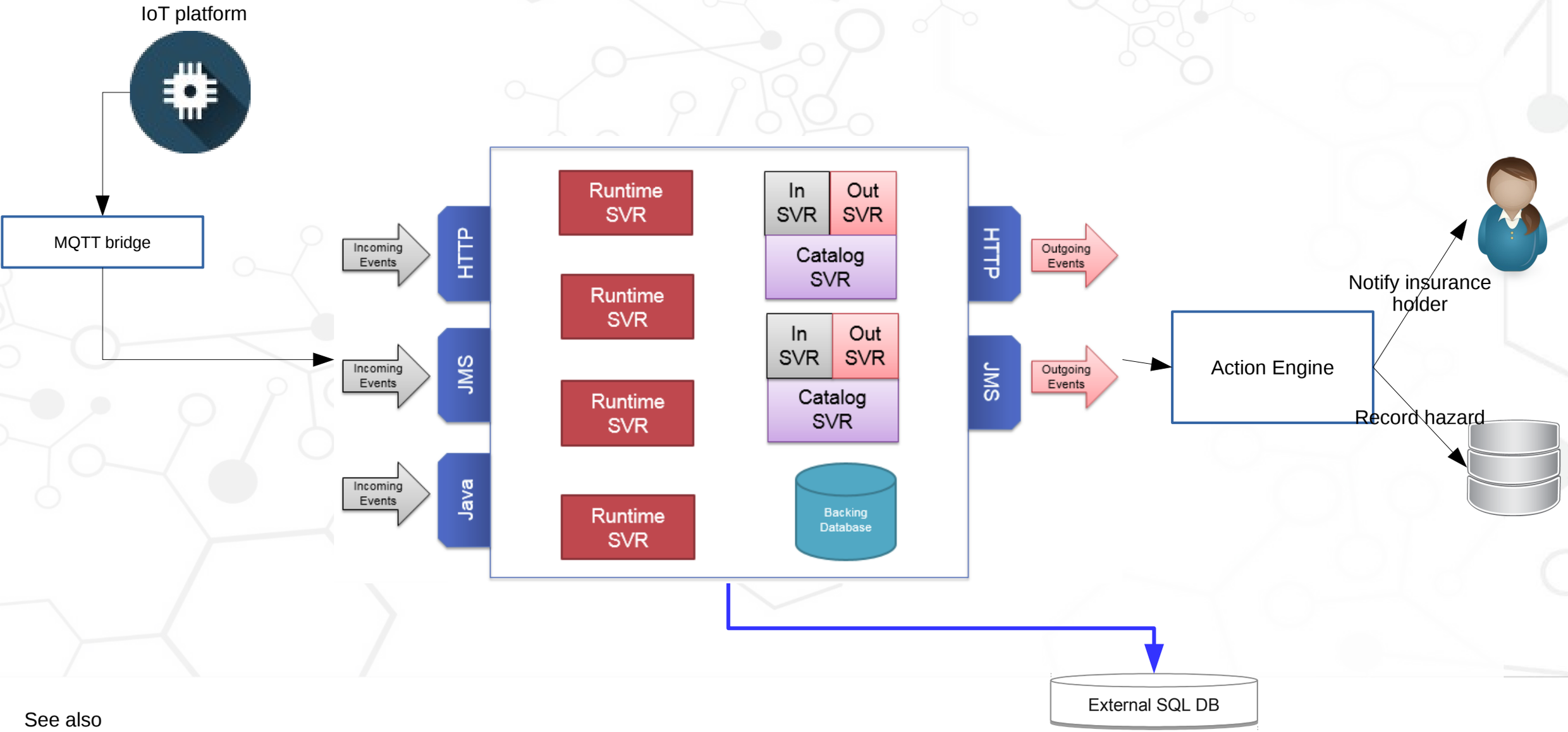
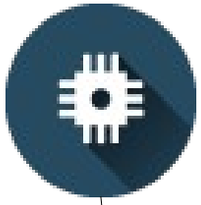


See also
https://hub.jazz.net/project/dselman/InternetOfInsight/overview

Approach #8: Real Time Insights

IBM Watson IoT



MQTT to Kafka bridge (part of IBM message hub)

User: Submit ruleset (translated into a stream of meta data)

```
$ ./bin/spark-submit --class org.apache.spark.examples.SparkPi \
    --master yarn \
    --deploy-mode cluster \
    --driver-memory 4g \
    --executor-memory 2g \
    --executor-cores 1 \
    --queue thequeue \
    lib/spark-examples*.jar \
    10
```

DevOps: Submit Kafka Consumer Jobs

Zookeeper

Message Hub (Kafka)

Consume and analyze Kafka topic event stream

Spark Driver Program

Spark Context

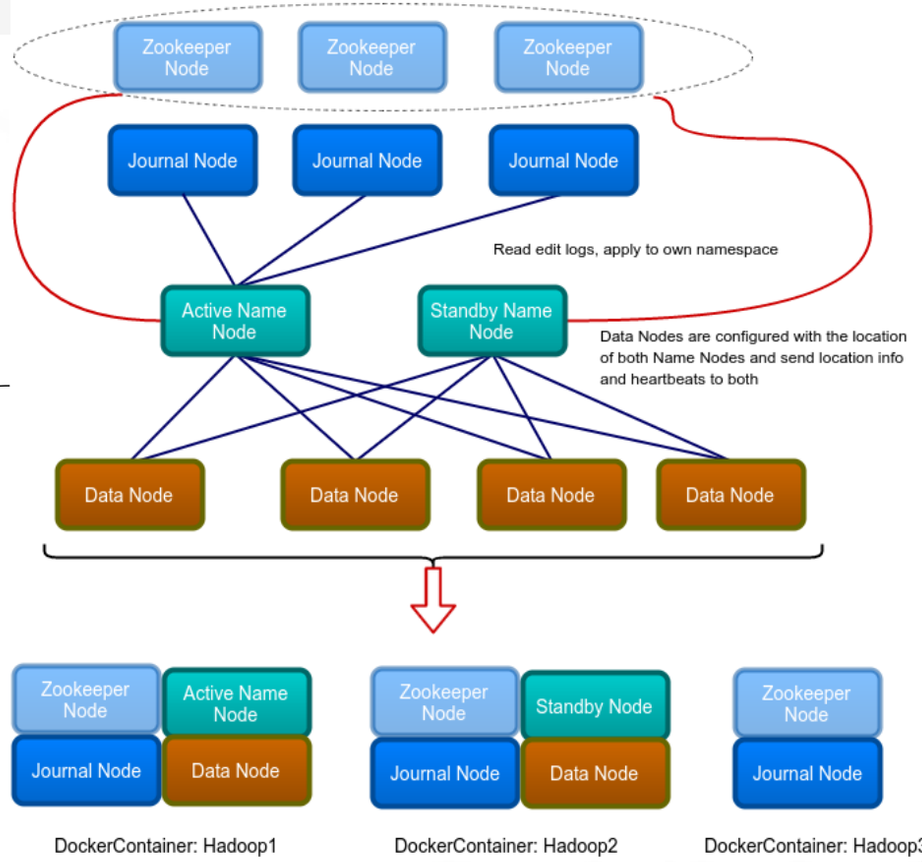
Instantiate Kafka Consumer Task

Rely on YARN for restart and on HDFS for Checkpointing

Spark Task

Spark Task Manager

Hadoop HA based on Quorum of Journal Managers and Zookeeper



DockerContainer: Hadoop1 DockerContainer: Hadoop2 DockerContainer: Hadoop3

RTI is built on Spark Streaming

Payload is processed according to Metadata. This is possible due to

For background see
http://spark.apache.org/docs/latest/streaming-programming-guide.htm
http://spark.apache.org/docs/latest/running-on-yarn.html

Decision Matrix "Must Have requirements"

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	"At least once" Fault tolerance, Back pressure	Partial ordering guarantee	"Exactly once"	Scalability (without affecting runtime)	Latency	Functional elements Stateful operators + Windows
Kafka shield engine	Yes	Yes	Maybe	By adding partitions and workers (online)	Low	No stateful sliding or tumbling windows
OpenWhisk shield dispatcher on Kafka	Yes	No	No	By adding partitions (online)	Medium due to OpenWhisk	No stateful sliding or tumbling windows
Apache Flink with Kafka connector	Yes	Yesb	Yes	Redeploy Flink CEP Program with higher parallelization (red-black)	Low	Yes
Spark Streaming on Kafka	Yes	Yes	No	Redeploy Spark Streaming program (red-black)	Medium due to micro-batching	Limited There are unmaintained packages available
Agent framework shield dispatcher on MQTT	Yes	Yes	No	Yes	*Low (according to their dev team)*	No stateful sliding or tumbling windows, no operators
IBM streams	Yes	Yes	Yes	Yes (online ?)	Low	Yes
ODM Decision Server Insights			Not known	Yes	Not known	Yes
Real Time Insight			No	Yes	See Spark Streaming	No stateful sliding or tumbling windows

Work in progress

Decision Matrix "Should Have requirements"

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	Modular CEP programming/ definition model	Modification without outage	Rule editor (no programming required)	Low Dev/Test Effort	Low TCO (Ops + Maintenance)	Automated Deployment	Cost
Kafka shield engine	Yes, shield expressed as javascript snippet	No	No	High Stateful Ops + Windows to be developed	Medium – only 2 components: Bluemix runtime + MessageHub service, but lots of custom code	Yes	Low
OpenWhisk shield dispatcher on Kafka	Yes, shield expressed as javascript snippet	No	No	High Stateful Ops + Windows to be developed	Medium – 4 components: BMX runtime + MessageHub + OpenWhisk + Redis + lots of custom code	Yes	Medium
Apache Flink with Kafka connector	Limited: Flink Kafka consumer job/group per shield (consuming the same topic)	No	No	Low	High – Flink is no BMX service, to be deployed as container/VM.	Only on Hadoop on docker/VM	Low
Spark Streaming on Kafka	No, all "shields" end up in a big java program (of Stream SQL expression)	No	No	Low	High – Spark service only avail in Dallas, so similar to Flink	Only on Hadoop on docker/VM	Low
Agent framework shield dispatcher on MQTT	Shield Java code must be run in Agent Container with explicit "state saving"	No	No	High Stateful Ops + Windows to be developed	High – to be deployed by IoT4I DevOps team	Not known	
IBM streams	No	No	Yes	Low	Low	Yes	High
ODM Decision Server Insights	Not known	Not known	Yes	Low	Low	No	High
Real Time Insights	Yes	Yes	Yes	Low	Low	Yes	

Work in progress

Selecting a candidate

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To render IoT4I profitable cost of supporting services and components should be as low as possible. This establishes ‘Cost’ as selection criterion with the highest priority and we end up with Spark and Flink

Latency and support for complex event processing clearly mark Flink as better choice

Build a prototype now

Halim: Flink is a true streaming platform. Spark is batching, but with small batches. You couldn't use Spark for high-speed financial trading, because you'd have to wait for quantities of information to arrive before you could do any processing. It's not clear to me why you would choose Spark now that we have ways of doing true streaming.

http://searchcloudapplications.techtarget.com/news/4500277396/Streaming-analytics-the-IBM-way-QA-with-Nagui-Halim

Prototype work

Goals, Scope/Timeline and Team

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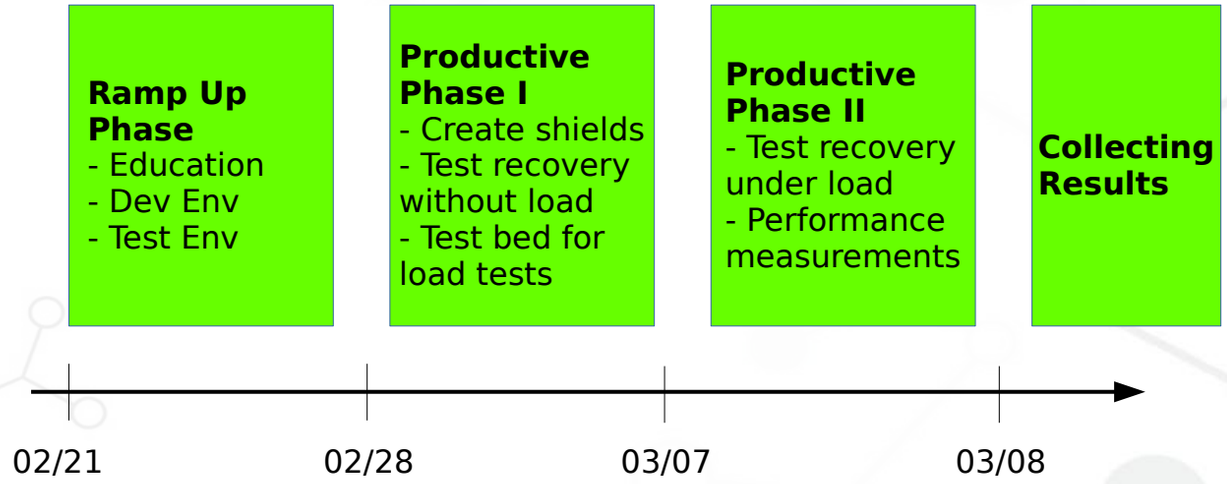
Goals

The prototype for a shield engine based on Apache Flink should

- Prove general feasibility of this approach
- Show proper recovery characteristics:
  “will the engine recover from an outage and resume work without loss of event or operator information ?”
- Gain some experience with sizing Flink and Hadoop with regard to event rate and event complexity.
- Get experienced with the operational aspects of Flink on Hadoop like monitoring, upgrade, backup/restore
- Serve educational purposes
  “learn about Big Data”

Scope

- Set up a docker based Hadoop/YARN environment that can be extended to be based on VMs
- Set up Flink 1.1.4 for standalone and YARN
- Provide a set up some shields to exploit stateful operators & windows
- Test for proper recovery (kill processes, kill containers)
- Load testing preparation – 4 shields with varying complexity, event rates from 10 to 100 evts/ sec
- Out: Fully automated setup
- Out: Investigate Apache Calcite as rule editor



Team

It’s Thomas, Patrick, Bilal & myself

Prototype: Setup

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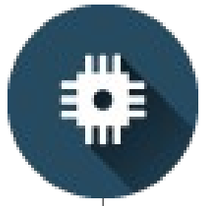
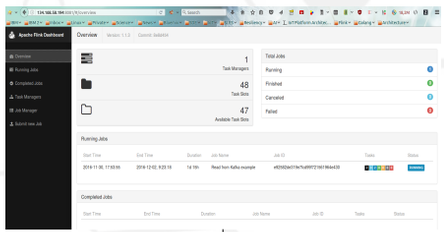


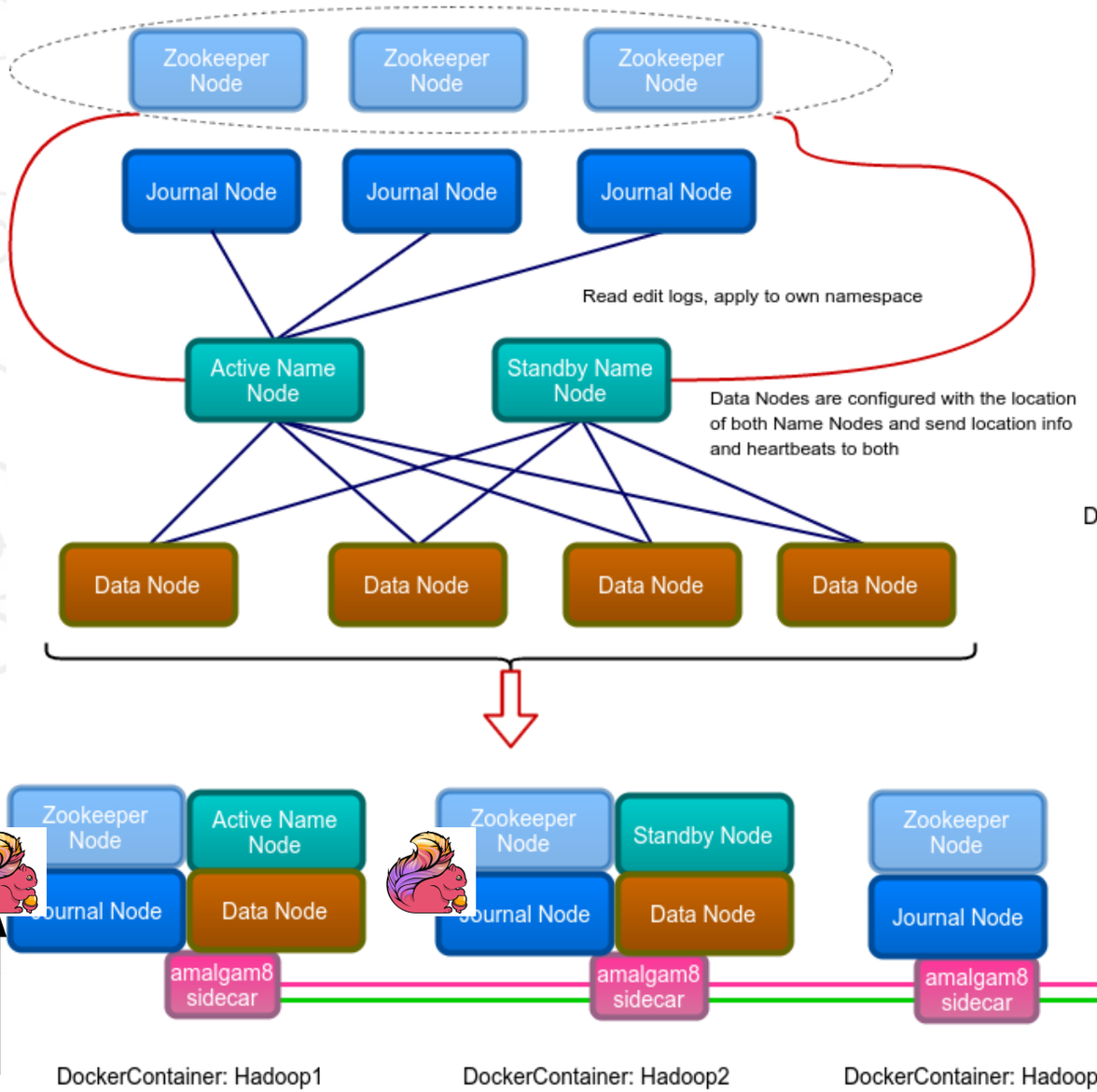
Consume and analyze
MQTT topic event stream

Notify insurance
holder

Action Engine



Submit Shield Jobs:
One MQTT Consumer Job per Shield !



THANK YOU!